Classification of the anatomy on 3D scans of human heads

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Problem

Is it possible to make a fully automatic system for classification of anatomical regions of frontal facial scans based on

- Randomized decision forests and
- Weak classifiers in the form of local 3D features?

Partial scans obtained from varying angles are stitched together. This requires manual annotation of overlapping regions.

Setup for obtaining partial 3D scans.

The data that lay out the foundation for the analysis comes from **the Danish Blood Donor Study** :

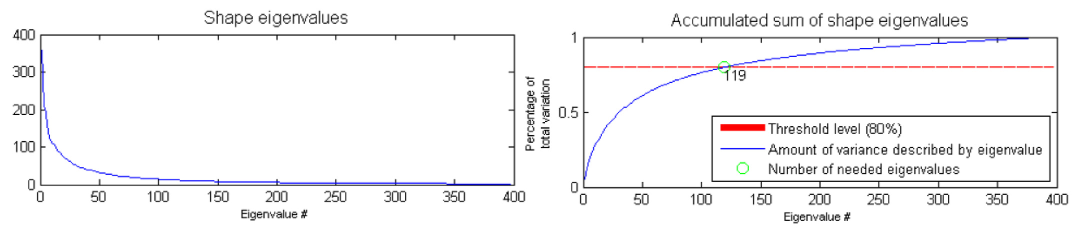
- Fronto-facial scans from 641 volunteers.
- Point-to-point correspondence between scans.
- Triangular mesh connectivity.

Assembled into an active shape model containing

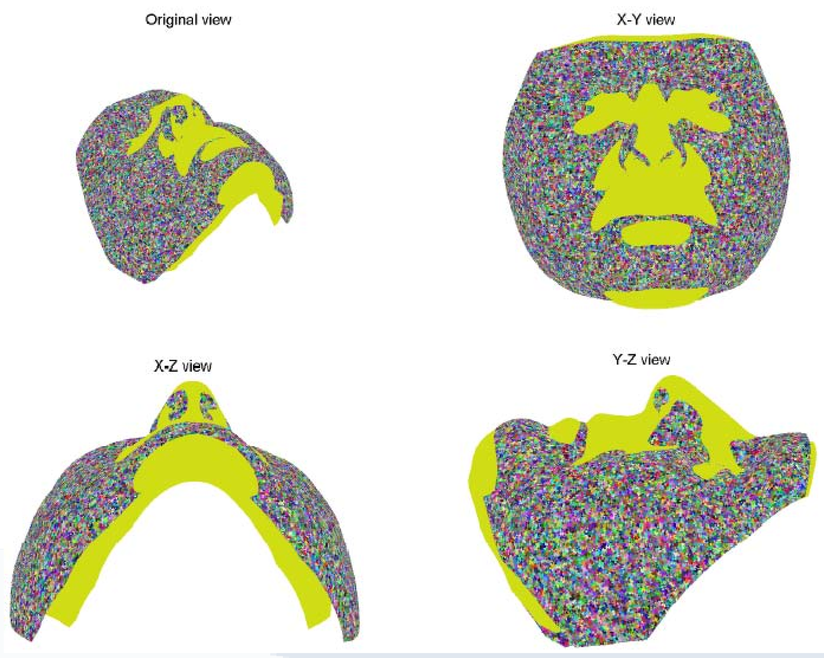
- 397 eigenvectors and eigenvalues.
- Vector represented mean fronto-facial shape.
- Mesh connectivity list.

$$\mathrm{x}(\alpha) = \bar{\mathrm{x}} + \Phi\sigma\alpha$$

Generating over 2000 3D representations of plausible frontal facial surfaces.



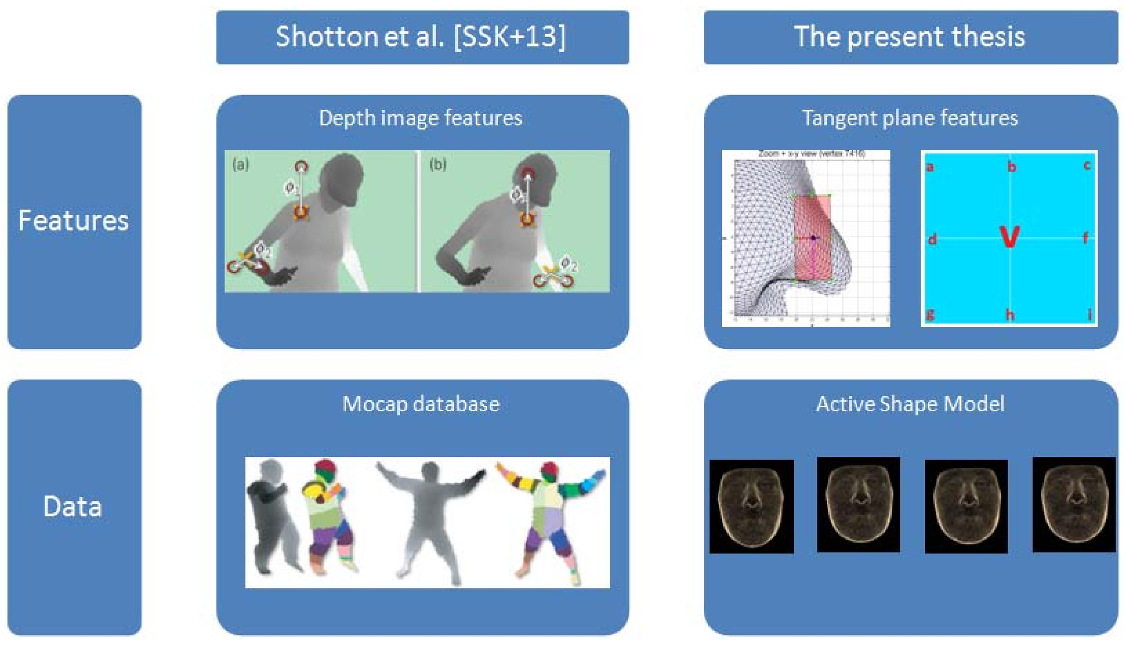
397 eigenvalues reduced to 119 to account for 80% variation.



Analysis

Inspired by Microsoft Kinect body-part classification system [SSK+13]:

Using randomized decision forests to label body-parts on depth images by using 2D features as weak classifiers.

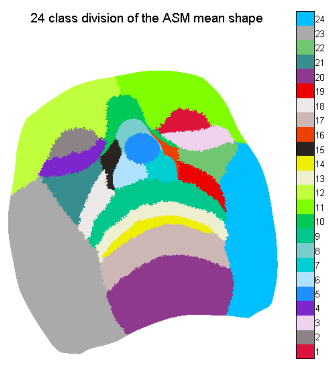


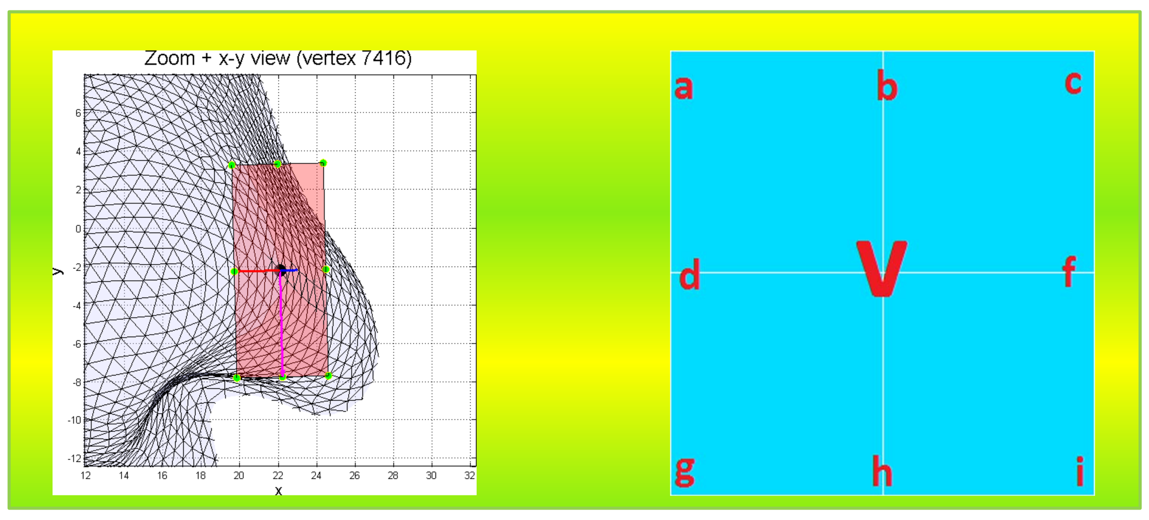
Tangent plane feature response function for a 3D vertex x and offset vectors u and v. $d(y)$ is the minimal distance from a point y to the mesh surface.:

$$f_\phi(I, x) = d_I(x+u) - d_I(x+v)$$

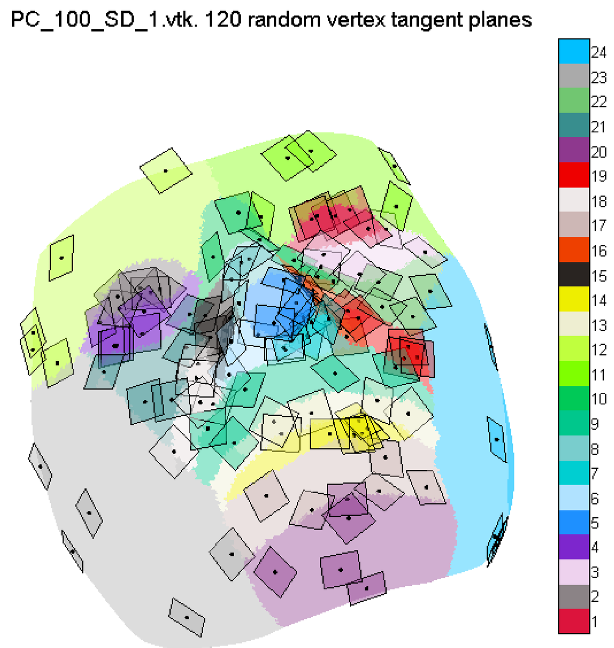
Using tangent plane features as weak classifiers for training randomized decision forests

- **The tangent plane features is a novel contribution.**
- 24 classes, or *ground truth labels*, have been manually annotated.
- 6 experimental computational setups with different foci (forest parameters, randomization degree, forest cascades, tangent plane feature dimensionality).
- Multi-scale feature computations vs. multiple, single-scale features.





The 3D **tangent plane features** describe local curvature by comparing pairwise minimal distance-to-surface for points distributed on the tangent plane based on tangent plane offset vectors (red and magenta on left figure). One tangent plane leads to 36 features (maximum number of distance pairs (a,b), (a,c), ⋯ , (h,i)).



Left: example showing:

- 1 training shape
- 5 samples from each class (120 in total)
- Tangent planes with unit scaled tangent vectors.

This leads to an observation matrix of size (120,36).

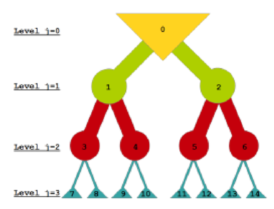
Bottom, left: Right column shows feature response for one vertex.

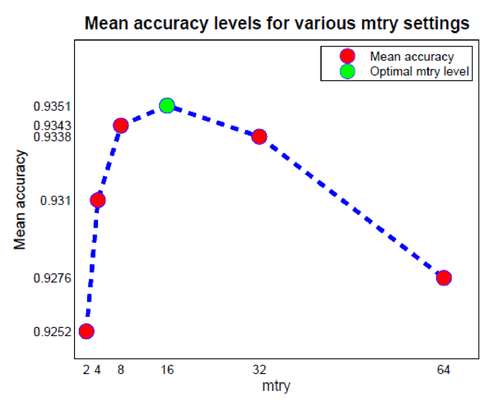
Bottom, middle: Feature response for all 120 observations.

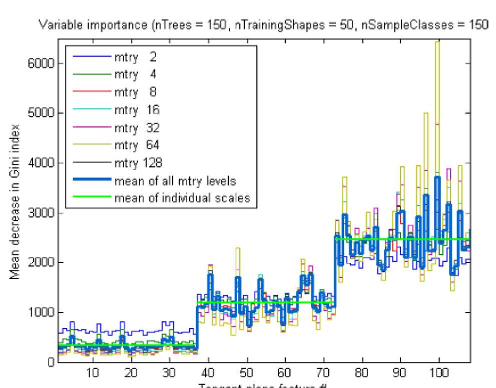
Bottom, right: ground truth class labels.

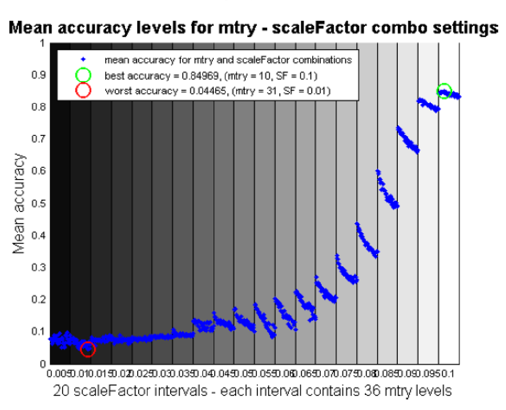
$(x+u, x+v)$	$d_I(x+u)$	$d_I(x+v)$	$f_\phi(I,x)$
(a,b)	0.4356	0.4296	0.0060
(a,c)	0.4356	0.9591	-0.5234
(a,d)	0.4356	0.5011	-0.0655
(a,v)	0.4356	0	0.4356
(a,f)	0.4356	0.5191	-0.0834
⋮	⋮	⋮	⋮
(h,i)	0.3507	0.5952	-0.2444

vertex ID \ $f_\phi(I,x)$	(a,b)	(a,c)	⋯	(g,i)	(h,i)	class
3613	1.0971	0.8992	⋯	-0.7631	-0.5983	1
16859	0.3909	-1.1980	⋯	0.3053	0.1749	1
⋮	⋮	⋮	⋱	⋮	⋮	⋮
8995	-0.6271	1.0901	⋯	-2.6292	-1.3669	2
9010	-0.0149	-0.6473	⋯	-0.1002	-0.8294	2
⋮	⋮	⋮	⋱	⋮	⋮	⋮
27584	-0.0458	0.0058	⋯	0.4416	0.3027	24
10783	-0.0482	0.2137	⋯	3.3530	-0.0371	24









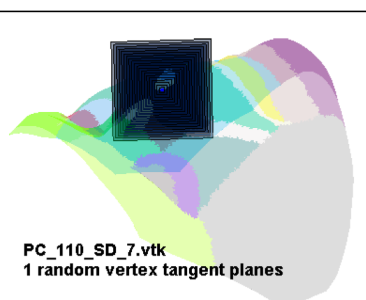
Top: Randomized decision forest made of multiple decision trees (basic tree concept shown).

Bottom: 20 scales of tangent plane features.

Right, top: Optimal forest randomization parameter of 16 out of 108 possible (factor 16/108).

Right, middle: Variable importance showing that the biggest feature scale shows higher variation in variable importance.

Right, bottom: Largest feature scale and a (10/36) factor gives a mean prediction accuracy of 85% (best). Second-smallest feature scale and a (31/36) factor gives a mean prediction accuracy of 5% (worst).



Discussion & Conclusion

The data

- The active shape model was based on a large amount of face scans and enabled the creation of a large database of plausible shapes, which is crucial when using randomized decision forests.

The tangent plane features

- The weak classifiers were scrutinized and tested for various parameters. The tangent plane features were scaled on basis of the bounding box diagonal length which was affected by the eigenvalue variation of the active shape model.

The randomized decision forests

- It was possible to train randomized decision forests with tangent plane features as input variables and the manually annotated ground truth labels as response variables.
- The data set allowed for testing on unseen fronto-facial shapes from the active shape model.

The experimental results spawned subsequent experiments

- Increasing randomization lead to improved predictive accuracy.
- Cascading classifiers did not improve results but a heuristic has been made that could potentially improve it.
- Frameworks for setting up multi-scale RFs and multiple, single-scale RFs were made. By scaling the tangent plane features by 10% of diagonal bounding box length and sampling 10 out of 36 features per internal node the highest accuracy of 85% was obtained.
- In one of the single-scale, single RF experiments, the test accuracy scored a 95%.

Future work

- Investigation of the relation between **local 3D facial feature abnormalities in terms of sparse principal components (spc)** and **tangent plane features.** It could be investigated if spc abnormalities could be detected by the use of tangent plane features and randomized decision forests.
- Use a full head active shape model to generate a new data set.
- The data used in the present work could be considered in a depth image context and the depth image features of Shotton et al. [SSK+13] could be used to train RFs.
- Cascades of classifiers by a combination of tangent plane features and depth image features.

References:

[SSK+13] Jamie Shotton, Toby Sharp, Alex Kipman, Andrew Fitzgibbon, Mark Finocchio, Andrew Blake, Mat Cook, and Richard Moore. Real-time human pose recognition in parts from single depth images. *Communications of the ACM*, 56(1):116–124, 2013.

Nicolas Tiaki Otsu obtained his degree as M.Sc. Eng. in Mathematical Modelling and Computation from DTU in April 2014.

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